

# DiaHalu: A Dialogue-level Hallucination Evaluation Benchmark for Large Language Models

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## Abstract

Though large language models (LLMs) achieve significant success in recent years, the hallucination issue remains a challenge, and numerous benchmarks are proposed for hallucination detection. Nevertheless, some of these benchmarks are not naturally generated by LLMs but are intentionally induced. Also, many merely focus on the factuality hallucination while ignoring the faithfulness hallucination. Additionally, although dialogue pattern is more widely utilized in the era of LLMs, current benchmarks only concentrate on sentence-level and passage-level hallucination. In this study, we propose DiaHalu, the first dedicated dialogue-level hallucination evaluation benchmark for LLMs to our knowledge. Initially, we integrate the collected topics into system prompts and facilitate a dialogue between two LLMs. Subsequently, we manually modify the contents that do not adhere to human language conventions and then have LLMs re-generate, simulating authentic human-machine interaction scenarios. Finally, professional scholars annotate all the samples in the dataset. DiaHalu covers four common multi-turn dialogue domains and five hallucination subtypes, extended from factuality and faithfulness hallucination. Experiments with the well-known LLMs and detection methods show that DiaHalu is a challenging benchmark, holding significant values for further research<sup>1</sup>.

## 1 Introduction

Large language models (LLMs) (Zhao et al., 2023b), addressing many downstream tasks through natural language generation (NLG) technique, achieve significant success across diverse fields of natural language processing (NLP) (Li et al., 2024a; Pan et al., 2024; Wei et al., 2023; Fan et al., 2023). With a considerable volume of parameters and sophisticated training methodolo-

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<sup>1</sup><https://github.com/ECNU-ICALK/DiaHalu>

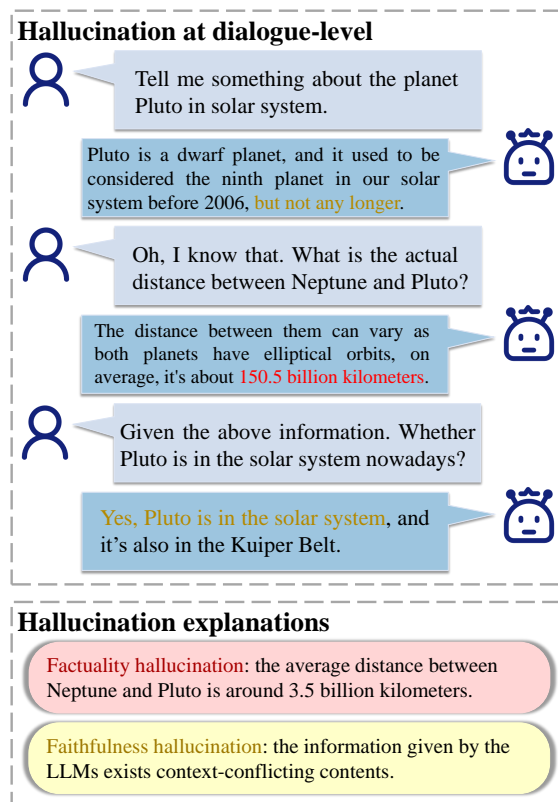


Figure 1: Our benchmark not only includes factuality hallucination but also incorporates faithfulness hallucination at the dialogue level, although most benchmarks overlook the latter one.

gies, LLMs significantly propelled advancements in artificial intelligence (Zhao et al., 2023b).

Despite many advantages of LLMs, the issue of hallucination remains a primary concern (Ji et al., 2023; Zhang et al., 2023c). Hallucination predominantly centers on the inclination of LLMs to generate nonsensical or untruthful contents for specific sources (Wang et al., 2023a). Therefore, the occurrence of hallucination poses risks to the application of LLMs in various real-world scenarios (Omiye et al., 2023; Wu et al., 2023b; Chen et al., 2024).

Given the aforementioned risks, hallucination de-

tection emerges as a highly crucial task. In recent years, researchers propose numerous benchmarks for hallucination detection task (Li et al., 2023b; Guan et al., 2023; Manakul et al., 2023; Yang et al., 2023). Nevertheless, several problems persist in these benchmarks. **(1) Not naturally generated.** One pitfall of existing benchmarks for detecting LLMs’ hallucination is that the hallucinated contents are typically induced via manually designed trigger prompts (Li et al., 2023b), while not naturally generated by LLMs as in daily usage (Liu et al., 2022). **(2) Merely focusing on factuality hallucination.** Most benchmarks merely focus on detecting factuality hallucination (Guan et al., 2023), with few datasets that can demonstrate faithfulness hallucination (Huang et al., 2023a) (Figure 1). Factuality hallucination emphasizes the discrepancy between generated contents and real-world facts. Faithfulness hallucination refers to the divergence of generated contents from user instructions or other inputs, as well as self-consistency within the generated contents, which tends to be ignored. **(3) Only concentrating on sentence-level and passage-level.** Researchers propose many sentence-level (Manakul et al., 2023; Zhao et al., 2023c) and passage-level (Yang et al., 2023; Feng et al., 2023b) hallucination detection benchmarks. However, the dialogue pattern has broader and more widespread applications in LLMs. More unique types of hallucination in dialogues make them more challenging to be detected (detailed explanations in Appendix A.12). Although it is rarely mentioned in previous researches, dialogue-level hallucination detection is equally essential.

Therefore, we propose a new **dialogue-level hallucination** evaluation benchmark for large language models (**DiaHalu**). We **initially** determine four domains for multi-turn dialogue: knowledge-grounded, task-oriented, chit-chat and reasoning. For each domain, we undertake a three-step process to construct the dataset. (1) We collect topics for dialogue from various sources, incorporate the topics into artificially designed system prompts and input them into two LLMs, enabling them to engage in a multi-turn dialogue. (2) Since the knowledge-grounded and task-oriented domains stand for real human-machine interaction scenarios, we align the contents of one of the conversational participants with human language. We manually modify the contents that do not conform to human language conventions and have LLMs re-generate, resulting in the final responses. (3) Professional scholars

Benchmark	By LLMs	Faith Halu	Multi Dia	Explanation
FactCollect	-	-	-	-
BEGIN	-	-	✓	✓
HADES	-	✓	-	✓
FactCHD	✓	-	-	✓
HaluEval	-	-	✓	✓
WikiBio+	✓	-	-	-
PHD	✓	-	-	-
Ours	✓	✓	✓	✓

Table 1: The comparison between our DiaHalu and other benchmarks. ‘By LLMs’, ‘Faith Halu’, ‘Multi Dia’, and ‘Explanation’ mean whether it is naturally generated by LLMs, whether it provides faithfulness hallucination, whether it is at multi-turn dialogue level, and whether there are explanations respectively (Appendix A.1).

annotate all the samples with labels, hallucination subtypes and locations, as well as explanations. It is noteworthy that we not only consider the factuality hallucination but also further classify the faithfulness hallucination into three types: Incoherence, Irrelevance and Overreliance. We similarly introduce the reasoning hallucination for the reasoning domain. The advantages of ours compared with previous benchmarks are listed in Table 1. **Additionally**, we conduct experiments on DiaHalu by deploying existing hallucination detection methods and some commonly used LLMs. The results indicate that DiaHalu is a highly challenging benchmark. Our contributions can be listed as follows:

- To our current knowledge, we propose the first *dedicated* dialogue-level hallucination detection benchmark for LLMs named DiaHalu.
- DiaHalu covers four multi-turn dialogue domains along with five hallucination subtypes extended from factuality and faithfulness hallucination, which are more widely applicable in real-world scenarios.
- The experimental results indicate that DiaHalu is a highly challenging benchmark for most LLMs and existing detection methods, holding significant value for further researches.

## 2 Related Work

### 2.1 Hallucination Detection Benchmarks

In recent years, researchers propose numerous benchmarks for hallucination detection.

In earlier years, hallucination detection benchmarks are primarily organized through manual

methods or generated via conventional language models. FactCollect (Ribeiro et al., 2022) is an artificially generated, multi-source factual hallucination detection benchmark. Muhlgay et al. (2023) collects error samples by instructing the language model based on pre-defined error types. HADES (Liu et al., 2022) and BEGIN (Dziri et al., 2022c) constitute hallucination detection datasets by conventional language model BERT (Devlin et al., 2019) and T5 (mostly) (Raffel et al., 2020) respectively. These benchmarks are not naturally generated by LLMs as in daily usage.

Consequently, some benchmarks are proposed to investigate the direct generation abilities of large language models. Zhao et al. (2023c); Fu et al. (2023); Chen et al. (2023a); Huang et al. (2023b); Zheng et al. (2023) enable LLMs to handle Question-Answer (QA) task and assess the factual accuracy of their responses. Concept-7 dataset used by Luo et al. (2023) evaluates whether a language model truly comprehends the meaning of each concept, thereby determining the presence of hallucination. FactCHD (Chen et al., 2023c) is generated based on natural language text and knowledge graphs (KGs). Mündler et al. (2023) employs a generative language model (gLM) to rewrite sentences according to the given context. New sentences compose a dataset that can evaluate whether the generated sentences exhibit knowledge-based self-contradiction hallucination. The aforementioned benchmarks mainly focus on detecting factuality hallucination (Guan et al., 2023), while ignoring the faithfulness hallucination (Huang et al., 2023a). The benchmark proposed in this paper extends to include faithfulness hallucination, that is, to evaluate the coherence and relevance of contents generated by LLMs.

Researchers also raise many sentence-level (Manakul et al., 2023; Zhao et al., 2023c; Guan et al., 2023) and passage-level (Yang et al., 2023; Feng et al., 2023b; Li et al., 2023b) hallucination detection benchmarks. Nevertheless, the dialogue pattern holds broader applications within LLMs. While previous researches rarely, to our current knowledge, propose a dialogue-level hallucination detection benchmark for LLMs. So, our DiaHalu is at the dialogue level.

## 2.2 Hallucination Detection

Current methods for hallucination detection (Tonmoy et al., 2024) can mainly be divided into four categories. (1) Model-based. This method in-

volves having the language models perform a classification task to determine whether hallucinated contents are present (Zhao et al., 2023a; Maharaj et al., 2023). (2) Retrieval-based. For the limited knowledge within the parameters of language models, we can detect hallucination by extracting or retrieving relevant knowledge from external knowledge graphs (Martino et al., 2023; Chen et al., 2023c) or web information sources (Béchar and Ayala, 2024). (3) Sampling-based. Another feasible method is to rewrite the generated contents to evaluate the consistency (Manakul et al., 2023; Zhao et al., 2023c; Zhang et al., 2023a). (4) Uncertainty-based. The mainstream view of this method (Zhang et al., 2023b; Gupta et al., 2024) is that ‘the lower the probability of generating a token, the more likely a model is to produce hallucination’.

## 3 The Overview of DiaHalu

### 3.1 Principles

The primary objective of this benchmark is to conduct hallucination detection in large language models. Hence, it is imperative to comprehend the meaning of *hallucination*. Hallucination predominantly centers on the inclination of LLMs to generate nonsensical or untruthful contents regarding specific sources (Wang et al., 2023a). The significance of hallucination detection lies in elevating the quality of text generation, preventing misleading information and misunderstandings, supporting applications within professional domains, etc. Therefore, to enhance the universality of our benchmark, it encompasses various multi-turn dialogue scenarios and multiple subtypes of hallucination, extending from factuality hallucination and faithfulness hallucination (Huang et al., 2023a).

### 3.2 Hallucination on Diverse Domains

We consider hallucination in diverse domains of multi-turn dialogue scenarios. Our benchmark covers a total of four domains, shown in Figure 2. Their specific descriptions are in Appendix A.2.

**Knowledge-grounded dialogue** is designed for users to engage in knowledge-based dialogue with LLMs (Ghazvininejad et al., 2018). The two speakers take part in a conversation about a knowledge-based issue.

**Task-oriented dialogue** is in a form of human-computer interaction, intending to accomplish a

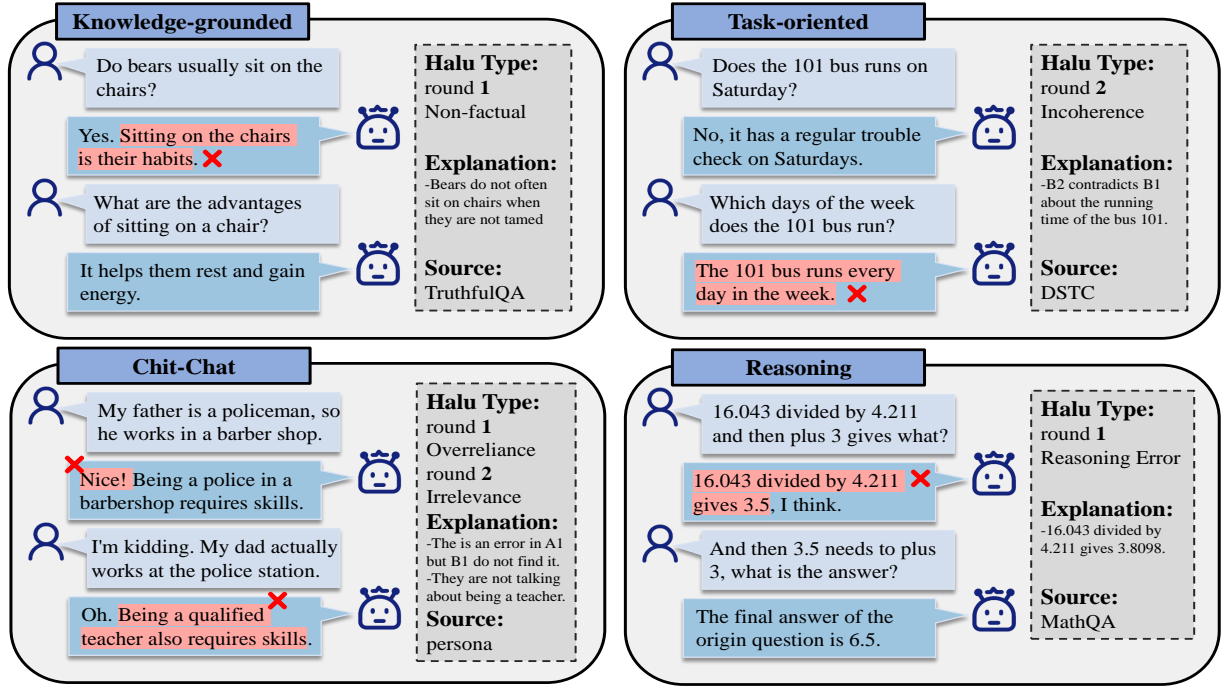


Figure 2: The demonstration of the DiaHalu benchmark, which covers four domains and five hallucination subtypes within dialogue-level scenarios. We also provide explanations and sources in the benchmark.

user-specified task (Wen et al., 2017).

**Chit-Chat dialogue** involves open-ended and non-goal dialogue (Sun et al., 2021). We provide two LLMs with personas and facilitate a dialogue between them.

**Reasoning dialogue** Following previous works (Chen et al., 2023b; Li et al., 2023a; Buszydlik et al., 2024; Grover et al., 2024; Zheng et al., 2023; Huang and Chang, 2023), we also treat reasoning errors as a kind of hallucination. We have the models discuss mathematical problems to achieve the answers (Kakarla et al., 2024).

### 3.3 Hallucination Taxonomy

We consider both factuality and faithfulness hallucination (Huang et al., 2023a). Based on Chen et al. (2023b); Wu et al. (2023a); Dziri et al. (2022b) and early works on text coherence (Wolf and Gibson, 2004; Atwell et al., 2024), we carry out a detailed classification of faithfulness hallucination into Incoherence, Irrelevance, and Overreliance. Meanwhile, we introduce Reasoning Error within the reasoning dialogue (Chen et al., 2023b; Li et al., 2023a; Buszydlik et al., 2024; Grover et al., 2024; Zheng et al., 2023; Huang and Chang, 2023). The example of each type can be referenced in Figure 2.

**Non-factual** implies whether it aligns with factual information.

**Incoherence** includes input-conflicting, context-conflicting and self-conflicting contents in the dialogue.

**Irrelevance** means that something unrelated to the topic of the conversation comes up.

**Overreliance** is that the LLM excessively trusts in the correctness of the context, generating responses for unanswerable contents (Slobodkin et al., 2023).

**Reasoning Error** covers all errors within the reasoning dialogue.

## 4 The Construction of DiaHalu

### 4.1 The Collection of Dialogue Topics

Since we confirm four domains for DiaHalu, the first step is to collect the topics for each dialogic domain.

For **knowledge-grounded dialogue**, we take into account world knowledge, factual knowledge, commonsense knowledge and multi-hop web knowledge. Therefore, we gather dialogue topics from TruthfulQA (Lin et al., 2022), CommonsenseQA (Talmor et al., 2019) and CWQ (Talmor

and Berant, 2018) datasets. There are also topics provided by GPT4 (OpenAI, 2023) and social media (including the authors). As for **task-oriented dialogue**, we primarily apply the most widely used MultiWOZ (MultiWOZ 2.1) (Budzianowski et al., 2018) which covers 7 real-life scenarios. To enrich the dialogue settings, we also consider the DSTC (DSTC 1.0) (Williams et al., 2013) dataset with a focus on bus routes. GPT4 and social media are harnessed to augment user behaviors and generate more dialogue occasions. We define the LLMs with personas primarily from Jandaghi et al. (2023) and facilitate an open **chit-chat dialogue** between them. Additionally, we make use of mathematical problems to assess the logical **reasoning dialogue** abilities of LLMs. These problems are sourced from GSM8K (Cobbe et al., 2021) and MathQA (Amini et al., 2019), both of which involve mathematical problems and solving processes encountered by middle school students.

The overall distribution of the above sources for dialogue topics is illustrated in Appendix A.3.

## 4.2 Dialogue Generation

Once finishing collecting the dialogue topics for each domain, we leverage ChatGPT3.5 and GPT4 to generate conversations in the format of self-dialogue. The complete process of dialogue generation is illustrated in Figure 3.

Initially, we integrate the dialogue topics into two system prompts, which are then inputted separately into two LLMs (both are ChatGPT3.5 or GPT4). These two system prompts guide the LLMs to generate  $N$  rounds of dialogue in a given domain and topic. More details of the system prompts can be found in Appendix A.4. Then, for knowledge-grounded dialogue and task-oriented dialogue, we manually examine all responses from A to determine their adherence to human language. For in both scenarios, we consider real human-machine interaction, aiming to assess the LLMs’ adaptability to genuine human behaviors. (We assume that A is the user and B is the LLM. In this setup, we ensure the accuracy of A and only annotate the contents of B.) The chit-chat dialogue and reasoning dialogue are relatively unconstrained and freely conducted, without incorporating any specific human-machine interaction settings (Section 3.2). They necessitate only their memory and comprehension capabilities regarding contextual information, thereby minimizing the need for manual intervention. Consequently, for the responses of A in knowledge-grounded and

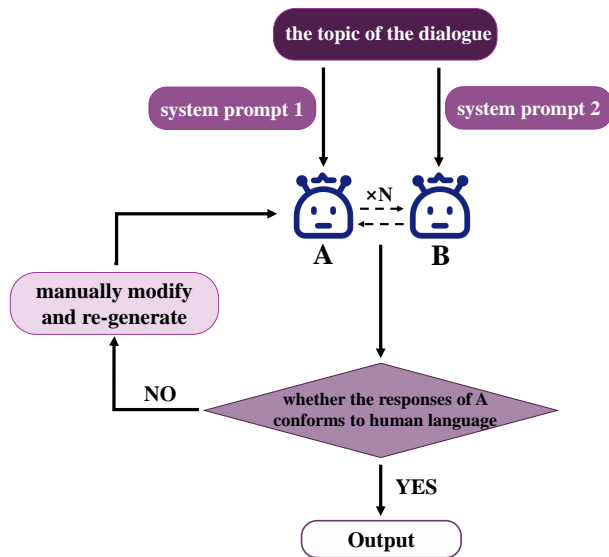


Figure 3: The complete process of dialogue generation.

Attribute	Attribute Value
Benchmark Name	DiaHalu
Generated by	ChatGPT3.5 / GPT4
Sample Form	dialogue-level
Sample Numbers	1103
Dialogue Rounds	6-10
Avg. Rounds	6.9120
Domain Numbers	4
Hallucination Subtypes	5
Max. Response Length (Words)	183
Avg. Response Length (Words)	13.2899

Table 2: The statistical information of the benchmark.

task-oriented scenarios, where the contents do not conform to human language, we manually modify and have LLMs re-generate. Eventually, we obtain the complete dataset of multi-turn dialogue.

We provide one output sample and more generation details in Appendix A.5. The statistical information of the whole benchmark is in Table 2.

## 4.3 Human Annotation

Annotating the hallucination and its types in this dataset is a very challenging task. Since there may be more than one instance of hallucination in multi-turn dialogue. Also, some hallucination subtypes in edge cases are difficult to differentiate. Therefore, the entire annotation process demands a high level of expertise from annotators and requires detailed definitions for ambiguous contents.

**The annotators** of our dataset are all seasoned researchers in the field of linguistics and natural language processing. We invite experienced experts in the field of LLMs’ hallucination detection from both academia and industry to engage in discussion and conduct sampling checks. For more details about the annotators and the experts, refer to Appendix A.6 (The annotators).

**Annotation process** is divided into three steps. (1) Each annotator labels some samples for each domain, followed by a careful discussion between the annotators and the experts. The discussions intricately define the application scope of each hallucination label (discussion results in Appendix A.7). (2) All the annotators label the entire dataset, discussions and corrections are made for inconsistent annotations. (3) Statistical analysis is performed on the annotated results. For more details, please refer to Appendix A.6 (The Annotation Process).

**Annotation Consistency** For evaluating the inter-annotator consistency, we calculate the Fleiss’s Kappa (Randolph, 2005) of Inter-Annotator Agreement (IAA) (Artstein, 2017), which is a statistical measure used to assess the degree of agreement among multiple raters for a set of items. The final score of Fleiss’s Kappa is 0.8842, representing almost perfect agreement among all the annotators. For more calculation details, please refer to Appendix A.6 (Label Consistency).

**Annotation Results** After annotating the entire dataset, we conduct several statistical analyses on it. Table 3 reveals the probability of hallucination occurring in each dialogue domain. The results indicate that hallucination are highly likely to arise in knowledge-grounded dialogue and reasoning dialogue. Therefore, the knowledge and reasoning abilities of LLMs still need further improvement. Despite LLMs’ powerful multi-turn dialogue capability, faithfulness hallucination such as irrelevance, incoherence and overreliance still persists. Figure 4 presents the proportion of each hallucination subtype in each dialogue domain. Irrelevance, incoherence, and overreliance widely exist in daily dialogue contexts, such as task-oriented and chit-chat scenarios. In knowledge-grounded dialogue, the factuality hallucination constitutes a significant proportion, while in reasoning dialogue, almost all hallucination are defined as errors in reasoning. This statistical information can help us understand the subtypes of hallucination in LLMs’ multi-turn

	Knowledge	Task	Chit	Reasoning	Overall
# Number	371	210	263	259	1103
# Non-Halu	199	135	164	129	627
# Halu	172	75	99	130	476
Halu Rate (%)	46.36	35.71	37.64	50.19	43.16

Table 3: The statistical information of hallucination on the four dialogue domains. ‘# number’, ‘# Non-Halu’, ‘# Halu’ and ‘Halu Rate’ represent the number of samples, the number of samples without hallucination, the number of samples with hallucination and the proportion of hallucinated samples.

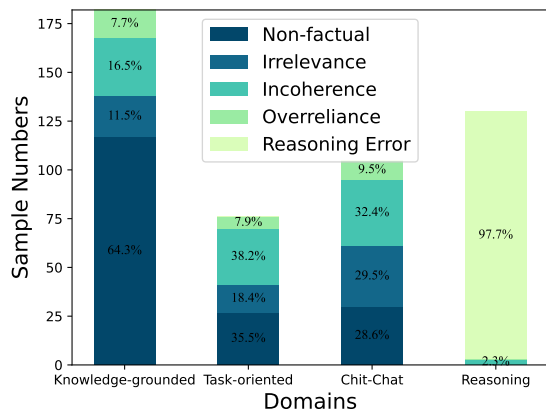


Figure 4: The distribution of five different hallucination subtypes within the four dialogue domains.

dialogue, facilitating an exploration of their origins and contributing to the elimination of these subtypes of hallucination.

## 5 Experiments

In this section, we assess the performance of several evaluation models and specialized methods on the dataset we introduced. Thereby, we can trial the effectiveness of existing methods in detecting dialogue-level hallucination. We still conduct more fine-grained detection and explore whether the phenomenon of hallucination snowballing exists.

### 5.1 Baselines

We select some powerful LLMs to detect hallucination by providing specific prompts. These models include open-source LLMs: LLaMa-30B (Touvron et al., 2023), Vicuna-33B (Chiang et al., 2023), and some closed-source LLMs: Gemini1.5 PRO (Anil et al., 2023), ChatGPT3.5 (Wu et al., 2023c) and GPT4 (OpenAI, 2023). Similarly, we also experiment on specialized existing hallucination detection methods, such as FaithCritic (Dziri et al.,

Method	Knowledge-grounded			Task-oriented			Chit-Chat			Reasoning			Overall		
	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1	Precision	Recall	F1
Random	41.57	43.02	42.29	31.86	48.00	38.30	38.46	50.51	43.67	49.61	49.23	49.42	40.72	47.06	43.66
<i>SelfCheckGPT</i> <sub>B</sub>	42.55	23.26	30.08	35.38	30.67	32.86	30.00	18.18	22.64	60.81	34.61	44.12	43.00	26.47	32.77
<i>SelfCheckGPT</i> <sub>N</sub>	59.46	25.58	35.77	38.84	62.67	<b>47.96</b>	45.19	47.47	46.30	70.58	18.46	29.27	48.65	34.03	40.05
<i>SelfCheckGPT</i> <sub>P</sub>	55.22	21.51	30.96	48.00	32.00	38.40	45.00	45.45	45.23	62.37	44.62	52.02	52.90	34.45	41.73
FOCUS	46.11	48.26	<b>47.16</b>	34.09	60.00	43.48	36.56	49.49	42.06	50.56	34.62	41.10	41.49	46.64	43.92
LLaMa-30B	37.50	5.23	9.18	30.77	5.33	9.09	50.00	11.11	18.18	81.25	10.00	17.81	49.33	7.78	13.43
Vicuna-33B	45.45	5.81	10.31	42.86	4.00	7.32	36.36	4.04	7.27	51.35	14.62	22.75	46.75	7.56	13.02
Gemini1.5 PRO	80.00	20.93	33.18	60.00	36.00	45.00	70.37	38.38	<b>49.67</b>	73.63	51.54	60.63	71.49	35.29	47.26
ChatGPT3.5	25.00	0.58	1.14	33.33	2.67	4.93	55.56	5.05	9.26	57.14	6.15	11.11	48.48	3.36	6.27
GPT4	80.89	31.98	45.83	74.19	30.67	43.40	67.74	21.21	32.31	74.07	61.54	<b>67.23</b>	75.21	37.61	<b>50.14</b>

Table 4: The classification results on four kinds of baselines, and the best F1 scores are in bold form. The indices *B*, *N* and *P* of SelfCheckGPT denote scoring with BERTScore, with NLI and using prompts, respectively.

Method	Knowledge-grounded			Task-oriented			Chit-Chat			Reasoning			Overall		
	Prec	Rec	F1	Prec	Rec	F1	Prec	Rec	F1	Prec	Rec	F1	Prec	Rec	F1
FaithCritic w/retrieval	28.26	84.54	42.38	-	-	-	-	-	-	51.63	79.17	62.50	-	-	-
Gemini1.5 PRO	80.00	20.93	33.18	60.00	36.00	45.00	70.37	38.38	49.67	73.63	51.54	60.63	71.49	35.29	47.26
w/ CoT	81.25	22.67	35.45↑	69.77	40.00	50.85↑	75.00	36.36	48.98↓	72.92	53.85	61.95↑	74.47	36.76	49.23↑
w/ one-shot	80.43	21.51	33.94↑	60.87	37.33	46.28↑	70.91	39.39	50.65↑	73.91	52.31	61.26↑	71.97	36.13	48.11↑
w/ retrieval	86.04	21.51	34.42↑	-	-	-	-	-	-	76.70	60.77	67.81↑	-	-	-
ChatGPT3.5	25.00	0.58	1.14	33.33	2.67	4.94	55.56	5.05	9.26	57.14	6.15	11.11	48.48	3.36	6.27
w/ CoT	45.45	2.91	5.46↑	33.33	2.67	4.94	40.00	4.04	7.34↓	47.06	6.15	10.88↑	43.18	3.99	7.31↑
w/ one-shot	40.00	1.16	2.26↑	42.85	4.00	7.31↑	46.15	6.06	10.71↑	56.25	6.92	12.32↑	48.78	4.20	7.73↑
w/ retrieval	70.00	4.01	7.69↑	-	-	-	-	-	-	70.58	9.23	16.32↑	-	-	-
GPT4	80.89	31.98	45.83	74.19	30.67	43.40	67.74	21.21	32.31	74.07	61.54	67.23	75.21	37.61	50.14
w/ CoT	86.05	21.51	34.42↓	73.17	40.00	51.72↑	80.56	29.29	42.96↑	71.43	76.92	74.07↑	75.38	41.18	53.26↑
w/ one-shot	81.42	33.14	47.11↑	71.87	30.67	42.99↓	72.22	26.26	38.52↑	73.11	66.92	69.87↑	75.09	40.55	52.66↑
w/ retrieval	77.89	43.02	55.43↑	-	-	-	-	-	-	74.40	71.54	72.94↑	-	-	-

Table 5: The results of CoT, the one-shot settings and the retrieval technique on the three closed-source LLMs. The ↑ and ↓ indicate whether these can promote improvements in F1 score. We also provide the detection results of FaithCritic with the retrieval technique.

2022a), SelfCheckGPT (Manakul et al., 2023) and FOCUS (Zhang et al., 2023b). For a detailed description of the above baselines, please refer to Appendix A.8 (I. Baselines Selected).

## 5.2 Metrics

For hallucination detection, we use standard binary classification to determine whether there exists hallucination (Table 4). We utilize binary classification evaluation metrics: Precision, Recall and F1. The positive label for this classification task is set as "Halu". Meanwhile, we also conduct more fine-

grained hallucination-type recognition to judge the specific subtype of hallucination and use micro-F1 score for all hallucination categories (Table 6). Appendix A.8 (II. Metrics Calculation) provides more thorough explanations.

## 5.3 Main Results

From the results in Table 4, we can get the following conclusions.

**First, DiaHalu is a highly challenging benchmark for dialogue-level hallucination detection.** Except for GPT4, the F1 scores of all other de-

	NF	Ic	Ir	Ov	RE	ALL
Gemini1.5 PRO	18.97	30.49	11.36	4.76	45.41	26.72
w/ one-shot	<b>19.74</b>	<b>32.53</b>	<b>11.49</b>	4.65	<b>46.24</b>	<b>27.96</b>
ChatGPT3.5	1.16	4.26	0.00	0.00	9.66	3.93
w/ one-shot	<b>1.18</b>	<b>4.35</b>	0.00	<b>6.45</b>	<b>10.96</b>	<b>4.64</b>
GPT4	29.38	25.00	5.71	4.65	55.66	32.30
w/ one-shot	<b>31.34</b>	21.95	<b>5.41</b>	<b>8.33</b>	<b>60.00</b>	<b>34.11</b>

Table 6: Fine-grained hallucination-type recognition F1 scores for three LLMs. ‘NF’, ‘Ic’, ‘Ir’, ‘Ov’ and ‘RE’ stand for Non-factual, Incoherence, Irrelevance, Overreliance and Reasoning Error, respectively. ‘ALL’ represents micro-f1 of all hallucination subtypes. We also incorporate a sample in the prompt to assist with the judgment. If the results in the one-shot setting show improvement, we bold them.

tection methods and detecting LLMs do not exceed 50.00. Existing LLMs, such as LLaMa-30B and Vicuna-33B, are not effective in accurately discerning most samples that involve hallucination. Regarding the specialized detection methods FOCUS and SelfCheckGPT (applying prompt and NLI methods), they achieve relatively better performances. However, it proves challenging with BERTScore for SelfCheckGPT.

**Second, ChatGPT3.5 shows a noticeable phenomenon of overconfidence.** Our dataset is primarily generated by ChatGPT3.5, which exhibits high confidence in its output. Despite providing a specially designed detection prompt, it still struggles to differentiate whether the dialogue content is hallucinated or not, not along the samples generated by GPT4. So, the majority of its output labels are "Non-Halu".

**Third, the faithfulness hallucination is more difficult to detect for LLMs.** Apart from the specialized hallucination detection methods, the results from directly harnessing LLMs for judgment indicate that the recognition accuracy for task-oriented and chit-chat domains of dialogue are much lower than that for the knowledge-grounded and reasoning dialogue. This is because the hallucination types in the knowledge-grounded and reasoning dialogue are primarily Non-factual and Reasoning Error, which present in a more direct and apparent manner. Nevertheless, task-oriented and chit-chat domains mainly consist of three subtypes of faithfulness hallucination, which requires a LLM to possess long-term memory and the ability to recognize topics/roles transition in dialogue.

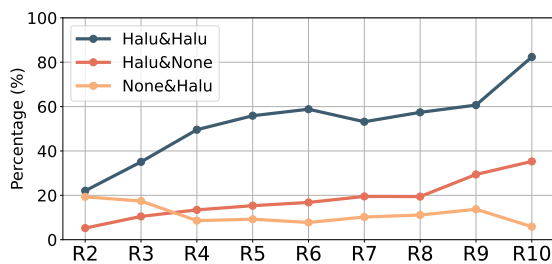


Figure 5: The proportions of the three dialogue round categories. For example, the three values of R7 denote the proportions of ‘these three categories in the 7th round’ within ‘hallucinated samples that have at least seven rounds dialogues’.

#### 5.4 Chain-of-Thought, One-shot and Retrieval for Detection

Chain-of-Thought (CoT) and Retrieval are two important techniques for enhancing the ability of LLMs. In this section, we test whether these two techniques can improve the effectiveness of hallucination detection in Table 5. More details are depicted in Appendix A.11. Meanwhile, we also incorporate a sample based into the vanilla prompt to test the few-shot capabilities of these three language models.

The experimental results indicate that all these three methods have facilitating effects on hallucination detection. However, Gemini1.5 PRO and ChatGPT3.5 with CoT show a decrease of around 1.00 F1 points in the chit-chat domain. We believe that these two models inherently lack the ability to recognize faithfulness hallucination, and additional CoT contents introduce noise to their judgments.

#### 5.5 Fine-grained Hallucination-type Recognition

Table 6 shows fine-grained hallucination-type recognition results for three open-source LLMs. We can conclude that ChatGPT3.5 fails the recognition of almost all labels. To some extent, Gemini1.5 PRO and GPT4 have the ability to recognize factuality hallucination and reasoning errors, but they have lower F1 scores for the three subtypes of faithfulness hallucination. This result reveals that faithfulness hallucination remains a pressing issue for LLMs. In the one-shot setting, all three models show improved accuracy in recognizing most labels. However, this setting also introduces some sample noise that interferes with the models’ judgments, such as GPT4 decreases its recognition F1 of the ‘Ic’ label.



## 5.6 Hallucination Snowballing

In this section, we study the hallucination snowballing phenomenon (Zhang et al., 2023c) in our benchmark. Specifically, for each round of dialog (2-10) in all hallucinated samples, we define three categories: **I** hallucination that appears in previous rounds and also appears in the current round (Halu&Halu), **II** hallucination that appears in previous rounds but not appear in the current round (Halu&None) and **III** hallucination that not appear in previous rounds but appears in the current round (None&Halu). We calculate the proportions of these three categories in Figure 5.

First, **I** is greater than the other two categories (**II** and **III**), which means that hallucinated contents are more likely to generate new hallucinated responses. Second, **I** shows the most obvious increasing trend, indicating that the probability of hallucination increases with the number of dialogue rounds. These two findings validate the hallucination snowballing phenomenon.

## 6 Conclusion

In this paper, we propose a dialogue-level hallucination evaluation benchmark named DiaHalu. We construct the benchmark in a three-step process. The DiaHalu covers four multi-turn dialogue domains and five hallucination subtypes. Experiments through some well-known LLMs and specialized detection methods on the benchmark show that it is a challenging task, holding significant value for further research (Appendix A.12).

## Limitations

This paper proposes a novel dedicated dialogue-level hallucination detection evaluation benchmark named DiaHalu. The benchmark covers four multi-turn dialogue domains and five hallucination subtypes. There is significant value for further research. However, two main limitations also exist. (1) During the second step of the benchmark construction phase, aligning the contents of speaker A with human language consumes a considerable amount of time and effort. Frequent calls to the ChatGPT3.5 or GPT4 API Keys result in a significant expense. Simultaneously, achieving consistency among all annotators led to prolonged discussion time and money cost. (2) We do not partition the dataset into training, validation, and test sets. The primary purpose of evaluation benchmarks is to assess a models' capabilities. However, if we

divide the dataset into the above three categories, this is about assigning capabilities to models. From the perspective of the two objectives, there is a clear difference. Another reason is that we need to consider the black-box detection scenario for those closed-source LLMs. However, if a division into these three types of datasets is necessarily required, it would require more data samples and larger resource consumption.

## Ethics Statement

The benchmark is primarily generated by ChatGPT3.5 or GPT4. We obtain all the API Keys through a paid subscription. All the annotators are real people and they receive corresponding compensation and rewards. The entire process and outcomes are free from intellectual property and ethical legal disputes.

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## A Appendices

### A.1 The Comparison with Other Benchmarks

In Table 1, we present the differences between DiaHalu and other hallucination detection benchmarks, highlighting the distinctive features that our DiaHalu is a naturally generated dialogue-level benchmark by LLMs, with various kinds of hallucination and explanations. All the compared benchmarks can be referred to in Section 2.1. HaluEval, WikiBio+, and PHD benchmark come from the paper [Li et al. \(2023b\)](#), [Manakul et al. \(2023\)](#) and [Yang et al. \(2023\)](#) respectively.

### A.2 The Four Dialogue Domains

**Knowledge-grounded dialogue** is designed for users to engage in knowledge-based dialogue with LLMs ([Ghazvininejad et al., 2018](#)). The knowledge includes world knowledge, factual knowledge, commonsense knowledge, and multi-hop web knowledge. It principally examines the accuracy of knowledge of the parameters in LLMs ([Petroni et al., 2019](#)).

**Task-oriented dialogue** is in a form of human-computer interaction, intending to accomplish a user-specified task ([Wen et al., 2017](#)). This type of dialogue system focuses on understanding the users’ task requirements and utilizes a LLM to provide relevant information or perform specific tasks accordingly.

**Chit-Chat dialogue** involves open-ended and non-goal dialogue ([Sun et al., 2021](#)). We provide two LLMs with personas and facilitate a dialogue between them. This approach allows for the evaluation of their memory capabilities, conversational coherence, and relevance to the information being discussed.

**Reasoning dialogue** centralizes on the logical reasoning and understanding capabilities of LLMs. Following previous works ([Chen et al., 2023b](#); [Li et al., 2023a](#); [Buszydlik et al., 2024](#); [Grover et al., 2024](#); [Zheng et al., 2023](#); [Huang and Chang, 2023](#)), we also treat reasoning errors as a kind of hallucination. We have the models discuss mathematical problems to achieve the answers ([Kakarla et al., 2024](#)).

### A.3 The Distribution of the Sources for Dialogue Topics

The number and proportion of all dialogue topics in DiaHalu across the 10 topic sources are shown in

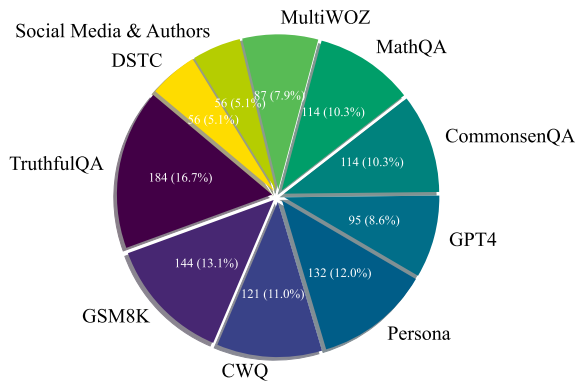


Figure 6: The distribution of the 10 sources for dialogue topics.

Figure 6. We use the hot topics of the social media, such as Facebook and Twitter, to obtain more topics in data generation process. GPT4 is used to augment and elaborate on the topics, scenes, and user behaviors. Take MultiWOZ dataset (which covers 7 real-life scenarios) as an example, we generate more real-life task-oriented dialogue scenarios via GPT4. As for the DSTC dataset with a focus on bus routes, we apply GPT4 to generate more potential user behaviors related to buses.

#### A.4 System Prompts for Dialogue Generation

In this section, we present the specific form of the system prompts for the four dialogue domains. We use ChatGPT3.5 (gpt-3.5-turbo-1106)<sup>2</sup> and GPT4 (gpt-4-1106-preview)<sup>3</sup> with the temperature 0.1. The brief system prompts of the knowledge-grounded dialogue, task-oriented dialogue, chit-chat dialogue and reasoning dialogue are respectively presented in Figure 7, Figure 8, Figure 9 and Figure 10.

Previous works prove the LLMs’ ability to follow complex instructions (Manakul et al., 2023; Guan et al., 2023; Chen et al., 2023b; Mündler et al., 2023; Li et al., 2023b; Wang et al., 2023b; Liu et al., 2023; Li et al., 2024b), including some hallucination tasks. Thus, we reference such kinds of prompts, and then we formulate prompts for our benchmark.

#### A.5 Generation Details and Data Format

We utilize 8 ChatGPT3.5 and 2 GPT4 API Keys, generating approximately 4000 examples in total initially. We conduct a thorough examination of samples to filter the confused formats or contents

<sup>2</sup><https://platform.openai.com/docs/models/gpt-3-5-turbo>

<sup>3</sup><https://openai.com/gpt-4>

not aligned with instructions (system prompts). To ensure a balanced number of positive and negative samples, we manually remove samples with highly similar semantics. Finally, the number of samples generated by ChatGPT3.5 and GPT4 are 748 and 355 respectively. The total number is 1103. The reason we use GPT4 to generate data is to ensure its competitiveness for a long time in the future.

Previous well-known hallucination benchmarks (Manakul et al., 2023; Guan et al., 2023; Chen et al., 2023b; Yang et al., 2023) contain 238, 400, 847, and 300 samples respectively, which is at the similar scale as ours. What’s more, our benchmark is at dialogue level, which contains about 7620 rounds (more than 27600 rounds initially) of interactions in total (6.9120 average rounds per dialogue as shown in Table 2). This indicates a larger volume of data compared to previous benchmarks at the sentence and passage levels.

It is also worth noting that, given that we assume the two subjects of the dialogue are A and B, both A and B are set to be either ChatGPT3.5 or GPT4, and it is not possible for one to be ChatGPT3.5 and the other to be GPT4.

Humans usually respond with flexible and brief expressions in dialogues, so we remove some GPT-specific generation patterns to better simulate natural human language. These patterns include special phrases like "I am an AI, so I cannot answer the corresponding question", detailed sectional explanations of a concept or method, excessively long sentences, and so on. Chit-Chat and Reasoning dialogue can also represent human-computer interaction. According to our preliminary studies, the formatting errors and GPT-specific generation patterns (mentioned above) are less likely to occur in these two types of dialogues, thus we skip the manual examination of whether A’s response adheres to human language, and focus on other examinations such as topic diversity.

We provide the specific format of one sample from the benchmark in Figure 11.

#### A.6 The Supplementary Details for Annotation

**The annotators** all obtain at least a bachelor’s degree, get a high score in IELTS or TOEFL exams, and are proficient in using search engines such as Google and Bing. The annotators are all seasoned researchers in the field of linguistics and natural language processing. In addition, everyone exhibits strong collaborative and communicative

**system prompt 1:**

### Your task is to generate a response based on the above conversation contents and the topic [TOPIC]. Your tone and way of thinking should be as similar to humans as possible. It is a part of a multi-round knowledge-grounded dialogue between A and B.

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response could be diverse and colorful, covering various fields such as literature, science and engineering, etc.
3. The response to be semantically rich and grammatically varied.
4. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
5. Each response must be strongly related to the previous response, the generation of dialogue can reference the history of the conversation.
6. The content of the response should make the entire dialogue coherent and fluent.
7. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.

**system prompt 2:**

###Your task is to generate a response based on the above conversation contents and the topic [TOPIC]. It is a part of a multi-round knowledge-grounded dialogue between A and B.

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response could be diverse and colorful, covering various fields such as literature, science and engineering, etc.
3. The response to be semantically rich and grammatically varied.
4. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
5. Each response must be strongly related to the previous responses, the generation of dialogue can reference the history of the conversation.
6. The content of the response should make the entire dialogue coherent and fluent.
7. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.

Figure 7: The brief system prompts for knowledge-grounded dialogue.

skills. We also invite senior experts in the field of hallucination detection from academia and industry to engage in discussions and data checking.

**The Annotation Process** To ensure the annotation quality, we perform three steps for annotation as described in Section 4.3 (Annotation process). **First**, each annotator labels around 50 samples for each domain. The annotators are required to label the presence of hallucination, hallucination subtypes and locations, along with the corresponding explanations. For cases of inconsistent annotation, we invite experts to provide suggestions in a discussion. After that, annotators specify the application scope of each hallucination label as needed. Then the annotators take a vote for resolving the label-inconsistency of the first 50 samples in each domain. **Second**, the entire dataset is annotated according to this standard. The annotators label all the rest samples and vote for the inconsistent samples, following data checks by the experts. **Third**, we conduct data statistics of the whole dataset.

In the first step above, the discussion is organized in the form of online meetings. Annotators provide the inconsistent-labeled samples to experts (first 50 in each domain), after which all annotators and experts agree on a time for an online meeting discussion. Experts provide suggestions, and

annotators modify the application scopes of hallucination labels based on the suggestions, thus making it more reliable.

**The Price** The annotation time for each sample ranges from 2 to 10 (average 6.2) minutes. We pay each annotator 0.5 US dollars for annotating a sample and pay each expert 0.5 US dollars for checking a sample. This exceeds the local average hourly wage. Through the aforementioned approach, the quality of the annotations and the value of the benchmark are ensured. Thus, we consider it is greatly contributory to propose such a benchmark.

**Label Consistency** After the whole annotation process, we achieve a label matrix  $\mathbf{L} \in \mathbb{R}^{N_s * N_A}$ .  $N_s, N_A$  represent the number of dialogue samples and annotators respectively. The calculation for Fleiss’s Kappa is shown below:

$$P_e = \left( \frac{\sum_{i=1}^{N_s} \sum_{j=1}^{N_A} \chi_{\{0\}}(\mathbf{L}[i, j])}{N_s * N_A} \right)^2 + \left( \frac{\sum_{i=1}^{N_s} \sum_{j=1}^{N_A} \chi_{\{1\}}(\mathbf{L}[i, j])}{N_s * N_A} \right)^2 \quad (1)$$



**system prompt 1:**

### Your task is to generate a response based on the above conversation contents and the topic [TOPIC]. Your tone and way of thinking should be as similar to customers as possible. It is a part of a multi-round task-oriented dialogue between A and B. And here are some related action of the you (which can be mentioned in the dialogue): [ACTIONS].

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response could be diverse and colorful, covering various fields such as literature, science and engineering, etc.
3. The response to be semantically rich and grammatically varied.
4. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
5. Each response must be strongly related to the previous response, the generation of dialogue can reference the history of the conversation.
6. The content of the response can be creative or personalized, design vague questions, quick topic switching, and repeated questions.
7. Give specific number information.
8. Use your imagination and global knowledge should also be included in the conversation.
9. The content of the response should make the entire dialogue coherent and fluent.
10. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.

**system prompt 2:**

###Your task is to generate a response based on the above conversation contents and the topic [TOPIC]. Your tone and way of thinking should be as similar to servers as possible. It is a part of a multi-round task-oriented dialogue between A and B.

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response could be diverse and colorful, covering various fields such as literature, science and engineering, etc.
3. The response to be semantically rich and grammatically varied.
4. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
5. Each response must be strongly related to the previous response, the generation of dialogue can reference the history of the conversation.
6. the service provider can refuse the customer's request, relying on your imagination to give the reason. The service provider can ask the customer for specific information.
7. Give specific number information.
8. Use your imagination and global knowledge should also be included in the conversation.
9. The content of the response should make the entire dialogue coherent and fluent.
10. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.

Figure 8: The brief system prompts for task-oriented dialogue.

$$P_o = \frac{1}{N_s} \sum_{i=1}^{N_s} \frac{\left( \sum_j^{N_A} \chi_{\{0\}}(\mathbf{L}[i, j]) \right)^2}{N_A * (N_A - 1)} + \frac{\left( \sum_j^{N_A} \chi_{\{1\}}(\mathbf{L}[i, j]) \right)^2 - N_A}{N_A * (N_A - 1)} \quad (2)$$

$$Fleiss's Kappa = \frac{P_o - P_e}{1 - P_e} \quad (3)$$

where  $P_o$  and  $P_e$  represent the relative observed agreement among annotators and the hypothetical probability of chance agreement respectively.  $\chi_y(Y)$  is the Indicator Function, which means when the value of  $Y$  is in set  $y$ , the whole function equals 1.

According to the above formulas, the calculated result for Fleiss's Kappa of our benchmark is 0.8842, representing almost perfect agreement among all the annotators.

**The Label Platform** We use Label Studio<sup>4</sup> for labeling, which is an online open-source data labeling platform in the field of artificial intelligence. The annotation interface is depicted in Figure 12.

### A.7 The Application Scope of Hallucination Labels

Annotating the hallucination and its subtypes in this benchmark is a very challenging task. One of the reasons is that some hallucination subtypes in edge cases are defiant to differentiate. Therefore, in the first stage of annotation, we provide detailed definitions for each hallucination subtype. Below are the results of the discussion between the experts and the annotators.

**Non-factual** implies that it does not align with facts or introduce elements that do not exist in real

<sup>4</sup><https://labelstud.io/>

**system prompt 1:**

### Your task is to generate a response based on the above conversation contents and your personas [PERSONA1]. Your tone and way of thinking should be as similar to personas as possible. It is a part of a multi-round chit-chat dialogue between A and B.

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response could be diverse and colorful, covering various fields such as literature, science and engineering, etc.
3. The response to be semantically rich and grammatically varied.
4. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
5. Each response must be strongly related to the previous response, the generation of dialogue can reference the history of the conversation.
6. The content of the response can be creative or personalized, design vague questions, quick topic switching, and repeated questions.
7. Give specific number information.
8. Use your imagination and global knowledge should also be included in the conversation.
9. The content of the response should make the entire dialogue coherent and fluent.
10. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.

---

**system prompt 2:**

### Your task is to generate a response based on the above conversation contents and your personas [PERSONA2]. Your tone and way of thinking should be as similar to personas as possible. It is a part of a multi-round chit-chat dialogue between A and B.

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response could be diverse and colorful, covering various fields such as literature, science and engineering, etc.
3. The response to be semantically rich and grammatically varied.
4. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
5. Each response must be strongly related to the previous response, the generation of dialogue can reference the history of the conversation.
6. The content of the response can be creative or personalized, design vague questions, quick topic switching, and repeated questions.
7. Give specific number information.
8. Use your imagination and global knowledge should also be included in the conversation.
9. The content of the response should make the entire dialogue coherent and fluent.
10. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.

Figure 9: The brief system prompts for chit-chat dialogue.

life.

**Incoherence** means there is a contradiction between one of the speakers and himself in the dialogue context, a contradiction between the two speakers (when both are declarative sentences) in the dialogue context. It also refers to factual and relevant nonsense, contextually inappropriate responses or other inconsistent errors.

**Irrelevance** involves responses that are irrelevant to the dialogue topic or an irrelevance due to misunderstanding the grammar of a question. (Please note that we emphasize the use cases for both interrogative and declarative sentences.)

**Overreliance** is that the LLM excessively trust in the correctness of the context, generating serious responses to statements that were inherently wrong or unanswerable (in a declarative sentence).

**Reasoning Error** covers all errors within the reasoning dialogue.

## A.8 Baselines and Metrics

### I. Baselines Selected

Below is a detailed description of all the baselines we selected.

**Random** A straightforward approach that randomly generates a label for each sample.

**FaithCritic** (Dziri et al., 2022a) is one of the most effective dialog text hallucination classifiers before the era of large language models. Trained on a large-scale dialog corpus, it can output the confidence level for each classification label. Since the model’s input includes dialog-related knowledge, we use the retrieved contents as the knowledge during the experiment.

**SelfCheckGPT** (Manakul et al., 2023) It is a widely used black-box hallucination detection

**system prompt 1:**

### Your task is to generate a response based on the above conversation contents and the problem [PROBLEM]. It is a part of a multi-round reasoning dialogue between A and B. You need to discuss your thoughts step by step to get the answer.

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
3. Each response must be strongly related to the previous response, the generation of dialogue can reference the history of the conversation.
4. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.
5. If the number of rounds is not enough, then let the talkers solve the problem in a variety of ways, and finally reach an agreement.
6. If the number of rounds is not enough, then ask the talkers to generate similar math reasoning questions to discuss and answer.
7. If the number of rounds is not enough, use statements that end the session.
8. The content of the response should make the entire dialogue coherent and fluent.

**system prompt 2:**

### Your task is to generate a response based on the above conversation contents and the problem [PROBLEM]. It is a part of a multi-round reasoning dialogue between A and B. You need to discuss your thoughts step by step to get the answer.

###The response must adhere to the following requirements:

1. The response must be within 3 sentences.
2. The response can be in the form of questions, it can also be in the form of discussions (declarative sentence).
3. Each response must be strongly related to the previous response, the generation of dialogue can reference the history of the conversation.
4. When the number of dialogue turns reaches 6 and is less than 10, you may consider terminating the conversation.
5. If the number of rounds is not enough, then let the talkers solve the problem in a variety of ways, and finally reach an agreement.
6. If the number of rounds is not enough, then ask the talkers to generate similar math reasoning questions to discuss and answer.
7. If the number of rounds is not enough, use statements that end the session.
8. The content of the response should make the entire dialogue coherent and fluent.

Figure 10: The brief system prompts for reasoning dialogue.

```
{
ID: 1,
Dialogue: "A1: Tell me about the solar system. \n B1: The solar system consists of the sun, planets, moons, asteroids,
and comets orbiting around the sun. \n A2: Tell me about Pluto. \n B2: Pluto is a dwarf planet in the Kuiper Belt, and it
used to be considered the ninth planet in our solar system before being reclassified in 2006. \n A3: Which is the eighth
planet? \n B3: Neptune. \n A4: What is the distance between Neptune and Pluto? \n B4: The distance between Neptune
and Pluto can vary as both planets have elliptical orbits, but on average, it's about 4.5 billion kilometers (2.8 billion
miles). \n A5: What is the distance between Sun and Pluto? \n B5: The distance between the Sun and Pluto also varies
due to their elliptical orbits. On average, it's about 5.9 billion kilometers (3.67 billion miles). \n A6: Which is closer
from Neptune? Sun or Pluto? \n B6: The Sun is closer to Neptune than Pluto. \n A7: Whether Pluto is in the solar system?
\n B7: Yes, Pluto is in the solar system. ",
Label: 1,
Hallucination Type: [[7,"Incoherence"]],
Domain: "Knowledge-grounded",
Explanation: ["B7 contradicts B2"],
Source: "Social Media",
Which LLM: "ChatGPT3.5"
}
```

Figure 11: One sample from our benchmark DiaHalu

framework. It rephrases the contents to be detected while ensuring the consistency of semantics by LLMs with different temperatures. Furthermore, it calculates the consistency between the original and the rephrased contents using five methods, thereby determining whether there exists hallucination. The

indices  $B$ ,  $N$  and  $P$  respectively denote scoring with BERTScore (Zhang et al., 2020), scoring with Natural Language Inference methods (He et al., 2023) and the direct judgment using prompts.

**FOCUS** (Zhang et al., 2023b) is an improved version of SelfCheckGPT. It takes into account the

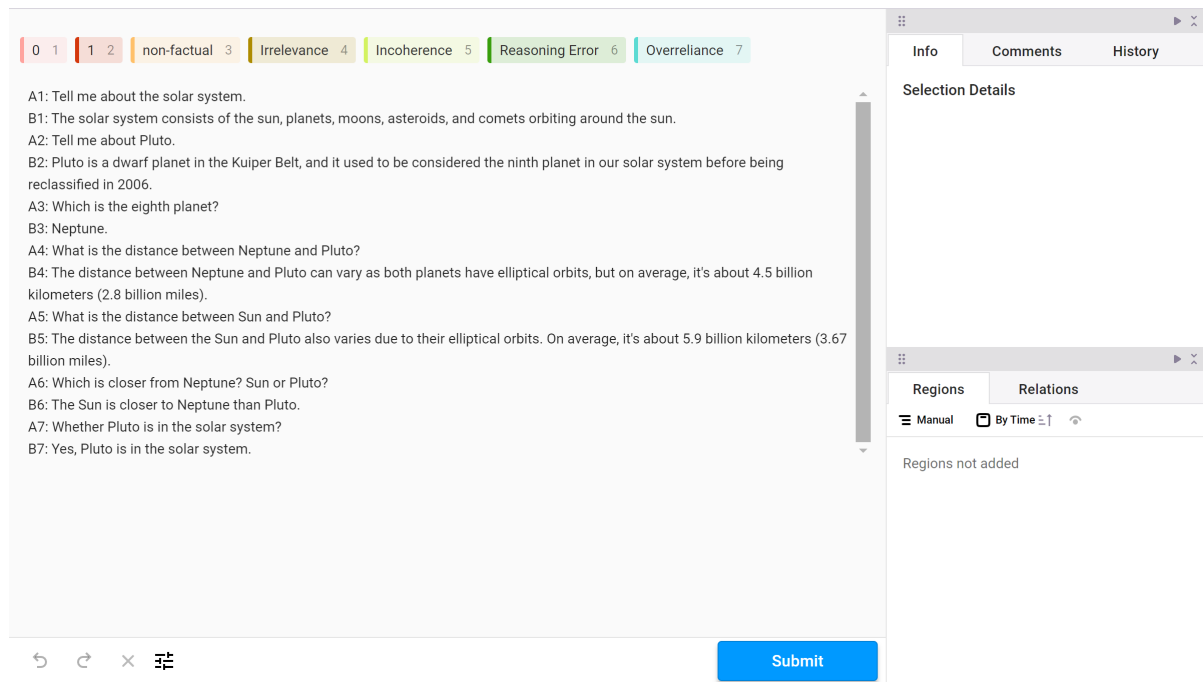


Figure 12: The annotation interface on Label Studio.

attention scores between entity tokens, enabling more accurate classification of hallucination at both the sentence and paragraph levels.

**LLaMa-30B & Vicuna-33B** They are two well-pretrained and widely deployed open-source LLM backbones<sup>5</sup> (Touvron et al., 2023; Chiang et al., 2023). We provide a specially designed prompt to assist with detection. More details about this prompt are shown in Appendix A.9.

**Gemini1.5 PRO** Gemini1.5 PRO<sup>6</sup> (Anil et al., 2023) is the latest version of the language model launched by Google. It inherits the powerful natural language processing capabilities of its predecessor and has made significant improvements in understanding and generating text. We employ the same prompt for binary detection as LLaMa-30B and Vicuna-33B do. We also create a manually prompt to assist with fine-grained recognition in Appendix A.10.

**ChatGPT3.5 & GPT4** Both of these models are developed by OpenAI<sup>7</sup>. ChatGPT3.5 marks the beginning of the era of large language models and GPT4 is currently the most powerful lan-

guage model (Wu et al., 2023c; OpenAI, 2023). We employ the same prompt as LLaMa-30B and Vicuna-33B do for binary detection. And the same prompt as Gemini1.5 PRO do is used for fine-grained recognition. The ChatGPT3.5 version is ChatGPT3.5 (gpt-3.5-turbo)<sup>8</sup> and the GPT4 version is GPT4 (gpt-4-turbo)<sup>9</sup>.

## II. Metrics Calculation

Despite we annotating the subtypes of hallucination in the dataset, achieving consistent labels even among humans requires further discussion. Therefore, similar to past hallucination detection efforts, we first focus on a binary classification task of determining the existence of hallucination. Consequently, we utilize binary classification evaluation metrics: Precision, Recall and F1. The positive label for this classification task is set as "Halu", for our main focus is testing the model's ability to recognize hallucination.

As for more fine-grained hallucination-type recognition, We define a correct judgment as one where both the presence of hallucination and the specific subtype of hallucination are accurately identified. For all label types, we use micro-F1 score to quantify the performances of the three classification models.

<sup>5</sup><https://huggingface.co/huggyllama/llama-30b>,  
<https://huggingface.co/lmsys/vicuna-33b-v1.3>

<sup>6</sup><https://gemini.google.com/>

<sup>7</sup><https://chat.openai.com/>

<sup>8</sup><https://platform.openai.com/docs/models/gpt-3-5-turbo>

<sup>9</sup><https://openai.com/gpt-4>

## A.9 The Prompt Designed for Detection

In Figure 13, we show the whole prompt specially designed for hallucination detection of the baselines: LLaMa-30B, Vicuna-33B, Gemini1.5 PRO, ChatGPT3.5, and GPT4. It is worth noting that due to the poor instruction-following ability and the disorderly output format of the LLaMa and Vicuna models, we conduct experiments in a 1-shot manner.

Previous works prove the LLMs' ability to follow complex instructions (Manakul et al., 2023; Guan et al., 2023; Chen et al., 2023b; Mündler et al., 2023; Li et al., 2023b; Wang et al., 2023b; Liu et al., 2023; Li et al., 2024b), including some hallucination tasks. Thus, we reference those prompts that classify hallucination using LLMs, and then we formulate prompts for ours.

## A.10 The Prompt Designed for Fine-grained Recognition

In Figure 14, we show the whole prompt manually created for fine-grained hallucination-type recognition of the three closed-source baselines: Gemini1.5 PRO, ChatGPT3.5, and GPT4.

## A.11 The Settings for CoT and Retrieval

Chain-of-Thought (CoT) (Feng et al., 2023a) describes the organized sequence of logical reasoning that unfolds during thinking. Retrieval (Gao et al., 2023; Ye et al., 2024) means retrieving relevant contents from the media to supplement external knowledge for LLMs. We employ CoT in all four domains to enhance the performance of ChatGPT3.5 and GPT4. The specific CoT is illustrated in Figure 15. Even so, only knowledge-grounded and reasoning domains are tested with retrieval via Google<sup>10</sup>. This is because domains of task-oriented and chit-chat mainly involve scenarios related to daily life or virtual worlds, without specific domain knowledge as supplementary information.

## A.12 Future Works

**The necessity of dialogue-level** The sentence-level, passage-level and dialogue-level hallucination differ in the hallucination types and detection difficulties. We will explain this with the following examples to make it more clear.

Here is a sentence-level hallucination example from the dataset FactCHD (Chen et al., 2023c). 'User: Can you tell me which mountain range is

longer, the Alps or the Pyrenees? LLMs: The Pyrenees are longer than the Alps.' In this sentence-level example, the LLM only responds to the user's question with one sentence. We need to assess whether there are hallucination in the single sentence generated by the LLMs.

Here is a passage-level hallucination example from the dataset WikiBio (Manakul et al., 2023). "Matthew Aylmer, 1st Baron Aylmer was an Irish soldier and colonial administrator. He was born in Dublin, the son of a barrister, and was educated at Trinity College, Dublin. ... He was buried in Westminster Abbey." This passage-level example is directly generated by the LLM. We need to determine whether the passage with multiple sentences involves hallucination. In this example passage, hallucination occurs in the last sentence which provides unfactual information. Since there are interrelations or dependencies between the sentences in the passage, passage-level hallucination detection is more challenging than the sentence-level one.

The examples of dialogue-level hallucination are shown in Figure 2, which covers four domains and five hallucination types. The differences between it with sentence-level and passage-level hallucination are as follows: **First**, more types of hallucination occur frequently in dialogue. One possible reason for most benchmarks merely focusing on detecting factuality hallucination is that they are organized at a sentence or passage level. In this setting, faithfulness hallucinations (including Incoherence, Irrelevance, and Overreliance) are less likely to occur. In contrast, since dialogue generation requires LLMs to have context coherence (Mishra et al., 2023), track the dialogue state (Heck et al., 2023), possess long-term memory capabilities (Zhong et al., 2024), and have the ability to recognize topic shifts (Lin et al., 2023), faithfulness hallucination (including Incoherence, Irrelevance, and Overreliance as described in lines 261-263) occur more frequently in dialogue. In our benchmark, the faithfulness hallucination mainly accounts for Task-oriented dialogue and Chit-Chat dialogue as shown in Figure 4. **Second**, it is more challenging to detect hallucination from dialogue than a single sentence or a passage. Since a dialogue contains multiple rounds of interactions that are interdependent, it can not determine whether the current round has hallucination merely based on the current content. For example, the Incoherence hallucination type occurs as the answer is not consistent with the previous context in the task-oriented dialogue in Figure 2. Thus,

<sup>10</sup><https://console.cloud.google.com/apis/library>

#Role:

Please tell me if there are any errors in the multi-turn dialogue I gave you.

#Some explanations about the multi-turn dialogue I input:

1. This is a multi-turn dialogue that occurs between A and B.
2. The multi-turn dialogue is [TYPE] type dialogue.
3. If the conversation type is either casual or reasoning-oriented, A and B are two people. In other cases, A is a person and B is ChatGPT, i.e., artificial intelligence.
4. Now, our subject for analysis is X, who can be either A, B, or both. X's conversational partner is another person. I want you to check for errors in [OBJECTS].
5. Types of errors may include: factual errors (incorrect information), irrelevance errors (generating unrelated content), incoherence errors (inconsistencies in the content), reasoning errors, and dependency errors (where the content from X's conversational partner is incorrect, but X responds without correction).
6. I will input each multi-turn dialogue gradually. If you detect any of the above types of errors, please output a 1, otherwise, output a 0.
7. Please judge each sentence carefully and check each sentence against its historical context.
8. Note that there is at least a 40% chance that the dialogues I provide will contain the aforementioned errors. Please help me carefully and thoroughly check them.

#Skills:

Please read the multi-turn dialogue I provide carefully.

Then output either 0 or 1, where 0 means no errors, and 1 means there are errors. Please do not output any other unrelated content. Just output either 0 or 1.

However, if I ask you to provide an explanation, please do so.

Figure 13: The whole prompt for hallucination detection of the baselines.

###Task:

Here is a multi-turn dialogue between A and B, which inevitably contains hallucination errors. I have categorized the errors into five types, with each category name and explanation listed below. Please read the dialogue from top to bottom and tell me what the first error type.

###Labels:

Non-factual: implies that it does not align with facts, introduce something that do not exist in real life.

Incoherence: means there is a contradiction between one of the speakers and himself, a contradiction between the two speakers(when both are declarative sentences), generating factual nonsense, other associative errors and inconsistency errors.

Irrelevance: involves responses that are irrelevant to the dialogue topic, or an irrelevance due to misunderstanding the grammar of a question.

Overreliance: give a serious response to statements that were inherently wrong or unanswerable.

Reasoning Error: covers all errors within the math reasoning dialogue.

###Output:

You only need to output a number from 0 to 4 representing the type of hallucination error.

0 stands for Non-factual.

1 stands for Incoherence.

2 stands for Irrelevance.

3 stands for Overreliance.

4 stands for Reasoning Error.

Here is the dialogue, please provide a number:

Figure 14: The whole prompt for fine-grained hallucination-type recognition.

it needs to analyze the context dependency in the whole dialogue and judge coherence, relevance and reasoning correctness, spanning multiple rounds of

interactions for dialogue-level hallucination detection, which is more challenging than sentence-level and passage-level detection.

Hallucination types may include:

1. Factual (errors in facts, mentioning things that do not exist in the real world)
2. Irrelevance (producing unrelated content)
3. Incoherence (inconsistency errors, contradictions between the generated content, including contradictions within the content generated for X, contradictions in the dialogue history of X, or contradictions between the content of X and the content of the entity X is conversing with)
4. Reasoning errors
5. Dependency errors (where the content of the entity X is incorrect, but X still responds without correction).

So please:

1. Check whether each response aligns with world knowledge, factual knowledge or common knowledge.
2. Verify whether each response is relevant to the overall conversation topic or the current context of the dialogue.
3. Examine whether the dialogue content contradicts with the preceding or following sentences or within itself.
4. Check for logical errors.
5. Examine whether each dialogue responds to incorrect content.

Figure 15: The whole CoT for the four domains of dialogue.

Therefore, it is necessary to construct a dialogue-level hallucination evaluation benchmark to promote research in LLM studies.

**Dialogue-level hallucination detection** is an important work in the future. We propose the first dedicated dialogue-level hallucination detection evaluation benchmark for LLMs and experimental results show that it is a very challenging task. Therefore, combining previous works (Chen et al., 2017; Deriu et al., 2021), developing methods based on this dataset to achieve a relatively high recognition accuracy is highly valuable.

**Dialogue-level hallucination elimination** is an extension task of this work. Most existing hallucination elimination methods primarily focus on sentence-level or passage-level factuality hallucination (Luo et al., 2024). Hallucination elimination at the dialogue level not only requires models to have much parameter knowledge, but also a long-context memory capabilities, the abilities to recognize changes in topics/roles and logical transitions in the dialogue. These are helpful in addressing faithfulness hallucination. At the same time, improving the accuracy of knowledge in the LLMs' parameters and the reasoning abilities are equally important.

**Hallucination snowballing** is the phenomenon that LLMs tend to accumulate hallucination rather

than self-correcting during the generation process (Zhang et al., 2023c). Some previous works validate this phenomenon (Azaria and Mitchell, 2023; Ang et al., 2023). In our benchmark, there is a noticeable issue of hallucination snowballing. Through the experimental results, we also display such phenomenon. This is because that LLMs are unable to perform timely self-check during generation, leading to the accumulation of hallucinations in multi-turn dialogues. Eliminating hallucination snowballing in LLMs is extremely urgent in the future.

**The Unanswerability of LLMs** During the annotation process of this dataset, we introduce a hallucination category termed "overreliance", which represents answering unanswerable content (Slobodkin et al., 2023; Sulem et al., 2021). This phenomenon signifies that LLMs tend to trust the input provided by users. Sometimes, even when there are errors in user input, the LLMs still fail to recognize them. A few past researches explore the related areas and try to find a solution. However, this issue in the application of human-machine interaction and multi-agent scenarios still remains crucial.